2023 International Conference on Recent Advances in Electrical, Electronics & Digital Healthcare Technologies (REEDCON) | 978-1-6654-9382-6/23/$31.00 ©2023 IEEE | DOI: 10.1109/REEDCON57544.2023.10150763

Energy Management in DC Microgrid Using Machine Learning

Margi Pandya
Electrical and Electronics Engineering
National Institute of Technology
Tiruchirappalli, India
pandyamk27@gmail.com

Ankur Singh Rana
Electrical and Electronics Engineering
National Institute of Technology
Tiruchirappalli, India
ankurranag@gmail.com

Aneesa Farhan M A
Electrical and Electronics Engineering
National Institute of Technology
Tiruchirappalli, India
aneesafma@gmail.com

***Abstract*—Integrating renewable energy sources, such as wind and solar, into microgrid operations can offer a range of benefits, including reduced transmission expansion costs, improved power quality, and lower costs. However, integrating these energy sources into microgrid operations can be challenging due to their unpredictable nature. To address this challenge, time series analysis is used to identify patterns and trends in past data to understand the underlying causes of changes in energy demand and supply. This information can be used to forecast future energy demand, supply and also help to optimise the operation of the microgrid. The power of solar or wind unit is forecasted using a one-class support vector machine, and a scheduling component is implemented using a heuristic method for optimal power production. This heuristic framework improves the accuracy of the machine learning algorithm. Hence, the system effectively addresses the challenges of managing microgrid challenges due to renewable energy sources, such as wind's unpredictable nature and solar power's impact on voltage profiles and frequency response.**

***Index Terms*—DC Microgrid, Machine learning, Energy Management, Solar, Wind**

I. Introduction

A microgrid (MG) is a small-scale electrical system that can provide electricity to a local area. It can be connected to the main grid or operated on its own. There are various types of energy sources that can be used in these MGs, such as fossil fuels and renewable energy sources. These energy sources can also be connected to the system through various topologies such as alternating current or direct current [1]. A hybrid type of MG combines an AC and DC source. Unlike other types of MGs, DC power in DC MG is easier to transmit and can be stored in batteries. Additionally, DC MGs can be easily integrated with DC-generating renewable energy sources like solar cells. DC MGs are better suited for use in MG applications because they can be controlled and optimized for a variety of load conditions. A DC MG uses DC power with improved efficiency and reliability compared to other types of MGs [2], [3]. The distributed energy resources (DERs) can be erratic and variable, makes managing power in MGs difficult [4]. It is possible to optimize the operation of MGs and enhance their efficiency and dependability by using machine learning (ML)-based techniques to forecast the output of DERs. Contrary to conventional methods, this can be accomplished by employing strategies like real-time scheduling of production and consumption and the use of energy storage systems to smooth out fluctuations in DER output [4], [5]. In MGs, ML-based management analyzes and predicts DER output using input data from field sensors. Support vector machine (SVM), a supervised learning algorithm type that can be trained on a dataset of historical wind and solar output data to make predictions about future output, is the strategy used in this paper [6], [7]. The SVM model may, however, have a high mean squared error, which can be reduced by fine-tuning the model's parameters with an optimization algorithm [8]. The MG's performance can be optimized to increase its effectiveness and dependability using predictions produced by ML algorithms. For instance, based on the predictions provided by the ML model, the (Supervisory Control and Data Acquisition) SCADA system could be used to regulate the scheduling of power from storage systems or to coordinate the operation of (DERs) [7]–[10]. SCADA systems can be used to enhance the integration of MGs with the main grid in addition to enhancing MG performance. SCADA systems can contribute to increasing the overall stability and reliability of the grid by offering real-time data about the operation of the MG.

This paper is classified into different sections; section II provides the details of Machine Learning Algorithms, section III gives insights about the methodology used in this work followed by the results section IV, the conclusion is described in section V.

II. MACHINE LEARNING ALGORITHMS

The proposed model for optimizing energy management in DC MGs involves three stages: i) time series analysis of data to understand the patterns and trends in the data ii) a machine learning-based stage for forecasting the output generation of wind and solar units, and iii) an optimization tool based on whale optimization algorithm (WOA) to aid in scheduling of these units.

A. Time Series Analysis

Time series analysis is a technique for analyzing and simulating the data gathered during the study period The data collected can be at regular or erratic intervals [11]. Time series data can be univariate (one variable) or multivariate (multiple variables). The power output of solar panels and wind turbines is predicted in this paper using a multivariate time series analysis.
Time series analysis involves several steps, including:

- Visualizing the data to identify any patterns or trends. This can be done using plots such as line charts or bar charts.
- Determining the statistical properties of the data, such as mean, variance, and autocorrelation.
- Identifying any underlying patterns or trends in the data, such as seasonality or cyclical patterns.

B. Support Vector Machine

A supervised machine learning algorithm called Support Vector Machine can be used to analyze datasets for classification or regression. The goal of Support Vector Regressor (SVR) is to establish the decision boundary or best fit line to generate the most precise predictions during regression. It seeks to maximise either the margin or the hyperplane's distance. The points on the hyperplane are called support vectors. This makes it easier to have good prediction ability, or the capacity to correctly forecast output for unobserved data without overfitting [6]. SVM can handle high-dimensional data and complex relationships between input features and output labels. Additionally, SVM can be trained efficiently and is not prone to overfitting (a problem where a model performs well on the training data but needs to improve on unseen data). In the case of regression, the SVM algorithm seeks to find the hyperplane that allows for the most precise predictions [7].

C. Whale Optimization Algorithm

In this paper a meta heuristic method, whale optimization algorithm is to reduce the objective function. An initial population must be created for the algorithm. Each candidate is called a whale, search for the optimal solution to a problem [7], [9]. The algorithm searches the population using a humpback whale's movement as a potential solution, which is represented by the whale. A combination of the current position, the best position thus far, and a random disturbance term is used to update each whale's position at each iteration. As long as the optimization algorithm's target value is met or the maximum number of iterations has been reached, the algorithm keeps looping. The whale's position that performs the best in the search space serves as the final solution.

1) *Mathematical Modelling*
Modeling of WOA [6] involves 3 steps such as Fig.1:

(a) Search for prey
In the search for prey phase, the humpback whales search randomly according to the position of neighbouring whales, and the best fit found until that iteration. The task to update the position of each whale is carried out using Eq.(1) and Eq. (2).

$$\vec{S} = |\vec{c}.\vec{D}_{rand} - \vec{D}(i)| \tag{1}$$

$$\vec{D}(i+1) = \vec{D}_{rand}(i) - \vec{A}.\vec{S} \tag{2}$$

(b) Encircling the prey
The encircling prey method assumes that the current best candidate solution (also known as the "prey") is close to the target solution. The position of other solutions (or "whales") is updated towards the best candidate solution using a set of equations designated as Eq.(3), (4), (5) and (6).

$$\vec{S} = |\vec{c}.\vec{D}_{best} - \vec{D}(i)| \tag{3}$$

$$\vec{D}(i+1) = \vec{D}_{best}(i) - \vec{A}.\vec{S} \tag{4}$$

$$\vec{A} = 2\vec{a}.\vec{x}_1 - \vec{a} \tag{5}$$

$$\vec{c} = 2\vec{x}_2 \tag{6}$$

where, i denotes the current iteration, $\vec{A}$ and $\vec{c}$ are coefficient vectors; $\vec{x1}$, $\vec{x2}$ are random vectors in the range [0, 1]; $\vec{D}(i)$ denote the position vector of a whale; and, $\vec{D}_{best}$ the position vectors of the best solution.

(c) Bubble-net attacking method
In the bubble-net attacking method, the shrinking encircling mechanism lowers the value of a $\vec{a}$ over several iterations from 2 to 0, and the spiral updating position method updates the position of each solution. In Eq.(7) and (8), the spiral updating position method is described.

$$\vec{S'} = |\vec{D}_{best} - \vec{D}(i)| \tag{7}$$

$$\vec{S}(i+1) = \vec{S'}e^{\mathrm{ml}}cos(2\pi l) + \vec{D}_{best}(i) \tag{8}$$

where $\vec{S'}$ is the distance between the best solution and the current position, The natural logarithm's base is e, and l is a random number in the range [-1, 1].

This strategy enables the algorithm to avoid getting stuck in local optima and to explore new areas of the search space. The algorithm iterates until one or more predefined stopping conditions—such as the number of iterations is equal to maximum iterations defined or an acceptable level of optimization—are met. The position of the whale that performs the best in the search space serves as the final solution.

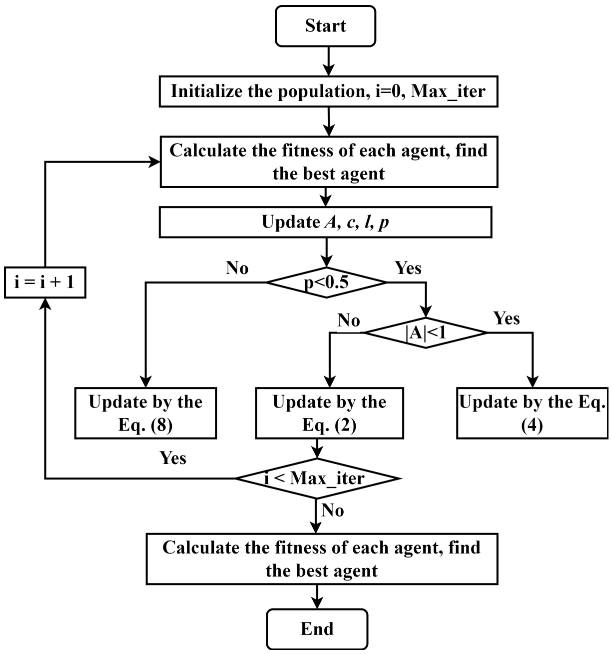


Fig. 1: Flowchart of WOA

III. METHODOLOGY

The libraries used in this model for data analysis and visualization includes; scientific computing (Numpy), data analysis (Pandas), data visualization (Matplotlib and Seaborn), machine learning (Sklearn), and preprocessing and performance evaluation (StandardScaler and Meansquarederror). Some of these libraries also provide functions for splitting datasets into training and testing sets generating random numbers (Random), and working with time-related data (Time).

Data preprocessing is required to understand the types and/or nature of the variables in data set, such as numerical, categorical and mixed. Extracting important features from the data to prevent the model from under fitting. Pre- proposing of data can be done in following steps:

- Missing data
- Descriptive Analysis of Data
- Time Series Analysis
- Wind Power Curve Analysis

A. Wind/Solar Power Forecasting

1) *Hourly Analysis for Wind and Solar Unit*
To conduct the hourly analysis, data is collected at regular intervals from a weather station from the current and voltage sensors to keep a account of power generated and organized in a spreadsheet or table. Thereafter, statistical measures such as average wind speed and direction, maximum and minimum wind speeds, and standard deviation for wind power dataset and features like irradiance, daily yield of power for solar power dataset are calculated. After calculating the statistical parameters, the feature of interest is grouped by the hour/month using the 'groupby' method in Pandas library. Mean is applied to the feature for example wind direction, wind speed or wind power for wind unit to compute the average for each hour. The resulting series is plotted using the plot method of matplotlib library. Interpret the results to gain insights about wind patterns and trends.

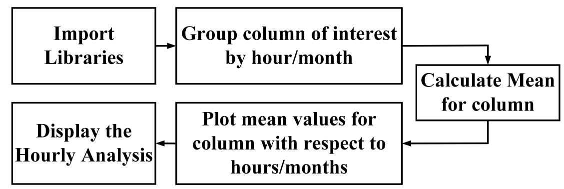


Fig. 2: Flowchart for hourly and monthly analysis

2) *Monthly Analysis for Wind and Solar Unit*
In order to perform monthly analysis of the data, a similar process as outlined in the flow chart in Fig.2 can be followed Specifically, the column in dataset is grouped by month and the mean values for active power generated is calculated and plotted using matplotlib and seaborn. These plots can then be displayed and given appropriate titles. By grouping the data by month and analyzing the mean values for different columns, it is possible to gain insights into trends and patterns in the data over time.
3) *Power Loss Curve for Wind*
The power loss curve, plotted as the difference between expected power output as specified by the manufacturer and actual power output generated. By understanding the patterns and characteristics of power loss, it may be possible to optimize the operation of the plant and minimize the cost of energy production. The power loss in a solar power unit is typically minimal due to the precise design of solar panels, which are engineered to maximize energy conversion efficiency and minimize energy loss.
4) *Analysis of Wind Power Curve*
A wind turbine's power curve depicts the relationship between output power and hub height wind speed. Analyzing the relationship between wind speed and power output for a wind turbine or wind farm is known as wind power curve analysis. In order to increase the system's effectiveness and dependability, this paper compares the expected power curve with the actual power curve and analyzes deviations from expected performance. The information can be used to forecast energy production, operate the wind farm more efficiently, and spot potential problems with the wind turbine.
5) *Directive Analysis for Wind*
A directive analysis is conducted to understand the directionality of wind patterns and their impact on wind power generation at a specific location. The analysis involved collecting data on wind direction and speed at the location

and analyzing the data to identify the predominant wind directions and the variations in wind direction over time.

IV. RESULTS AND DISCUSSIONS

In this paper, a microgrid system, as depicted in Fig. 3, consists of renewable energy sources like solar panels or wind turbines, as well as a storage system having batteries, to store any excess energy for later use. The conversion of power to AC/DC is done using power electronics converters like inverters, choppers, and rectifiers. The efficient distribution and use of power within the microgrid system is made possible by convertors as the loads, the standard electrical devices and appliances can be supplied by either of AC or DC type. In this paper, the MG system is wired into the grid (on grid).

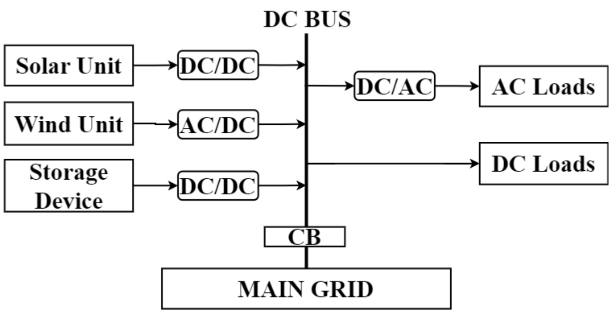
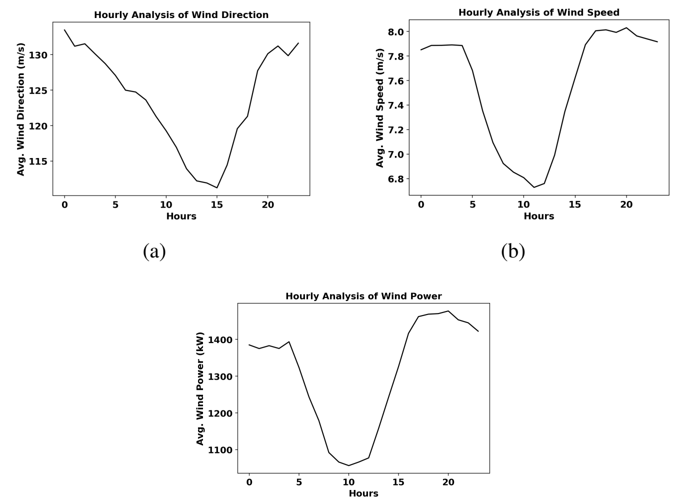


Fig. 3: DC Microgrid

The output power generation using SVR model for a DC microgrid, with and without the use of the optimization algorithm for sample datasets of wind power plant [12] and solar power plant [13] is shown in this paper. The results of this analysis show the design and implementation of an energy management system for the DC microgrid, aiming to optimise its operation and maximise the utilisation of renewable energy sources.

A. Wind Unit

1) *Hourly Analysis*
An hourly analysis for wind direction, wind speed, and wind power is shown in Fig. 4 (a), (b) and (c), respectively. There is a similar trend in wind speed and wind power curves. Specifically, the average wind speed and power output remain constant before the 5th hour and after the 15th hour. The relationship observed here is as expected according to Betz equation, which defines the relation between the wind power and speed as power of three. The maximum wind power is 1600kW produced occurs when the wind speed reaches 8.5 m/s and minimum of 1050 kW at the speed of 6.74 m/s. The maximum power produced is not equal to the rated power this might be due to inevitable losses due climate changes, such as; abrupt variations in wind speed or due to malfunctioning of wind turbines. Below a wind speed of 3.5 m/s, no control is produced. However, a 15.2% drop in wind



(a) (b) (c)

Fig. 4: Hourly Analysis for (a) Wind Direction, (b) Wind Speed and (c) Wind Power Generation

speed resulted in a corresponding drop of 24.4% in active power. These findings suggest the operation of the unit is as expected theoretically.

2) *Monthly Analysis*
Fig. 5 shows the monthly analysis of the wind power data that the highest power of the corresponding month in the considered duration is 1750 kW is produced during the months of March and November, while the lowest power of 750 kW is made during the month of July. This suggests that seasonal variations in wind conditions influence the power output of the system. Additionally, understanding these variations in power output can be helpful in planning and managing the system's operation.

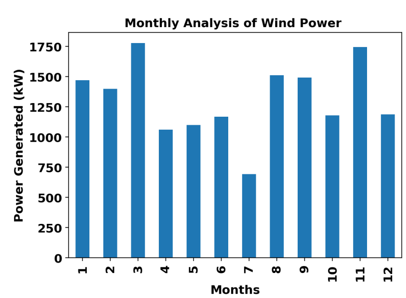


Fig. 5: Monthly Analysis of Active Power Generated

3) *Wind Power Curve Analysis*
The line plot in Fig. 6 compares a wind unit's "Ideal Power" and "Produced Power" as wind speed rises. This

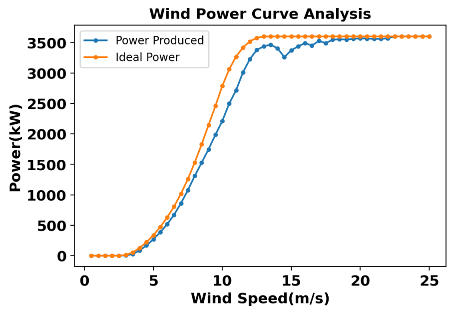


Fig. 6: Wind curve analysis for expected and actual wind power

is known as a wind power curve. The design of the wind turbine including the size, shape, and type of its blades as well as the system's overall efficiency can both have an impact on this curve's shape. Based on the results of this analysis, the wind unit could not produce as much power as was specified by the manufacturer, which resulted in a loss. A wind speed of 3.5 m/s, which can be considered as a threshold for power generation, was also too low for the wind turbine to produce any power.

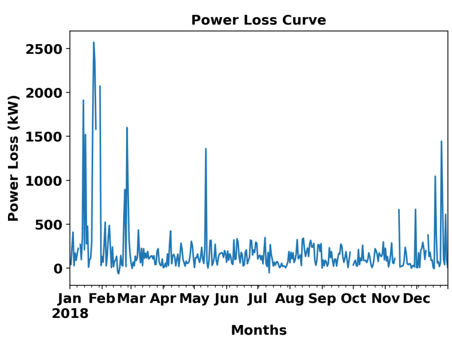


Fig. 7: Plot for Power Loss Curve for Wind Unit

The power loss curve exhibited in Fig. 7 shows deviations from an expected performance at certain times, including during certain days in January as well as at the beginning of March and end of December. These deviations may be caused by various factors, including damage to the system or issues with the maintenance and servicing of the plant or due to malfunctioning of various components of the plant.

4) *Directive Analysis*
The directive analysis showed that the predominant wind direction for optimal power production was SSW (south-southwest) at a speed of nearly 11 m/s. These findings suggest that the wind conditions at this location that are favourable for wind power generation, with a dominant wind direction and speed that can produce the significant power output. This also help in further design of new wind turbines for future expansion in the plant.

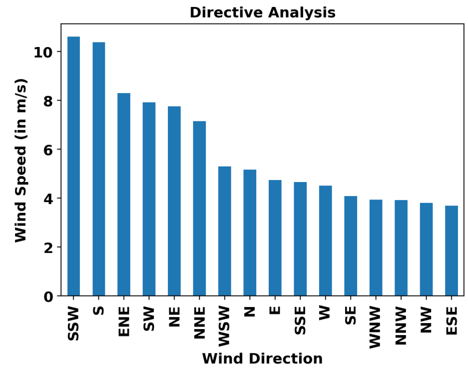


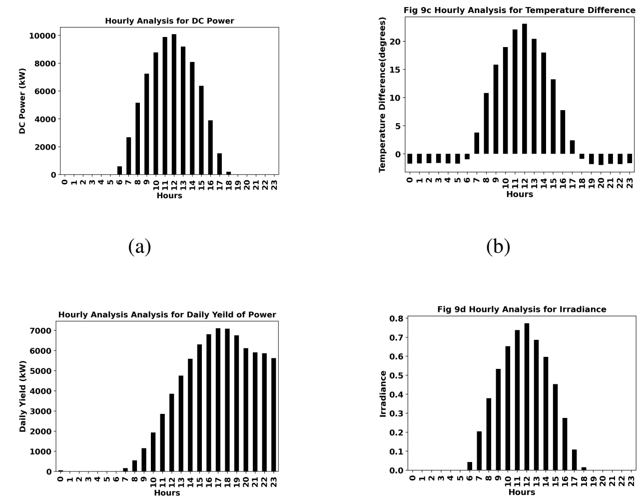
Fig. 8: Plot for Directive Analysis for Wind Unit

B. *Solar Unit*

1) *Hourly Analysis*
An hourly analysis of weather and generation data was conducted for a solar unit and plotting the resulting graphs are shown in Fig. 9. DC power is produced for 12 hours from 6:00 AM to 6:00 PM. The maximum solar power of 10MW is produced during the noon time when the irradiance is maximum. During the morning and evening hours when solar irradiance is almost nil similar trend is observed in the output power too. The excess power produced during these 12 hours should be stored to meet the demand during peak hours. This relationship suggests that the dc power generated is influenced by the amount of irradiance received by the plant. The average daily yield of the plant for complete duration is plotted in Fig. 9 (c) As observed in the hourly analysis for generated power, the cumulative yield is also increased after 6:00 AM.
The temperature difference, which is the difference between the temperature of the solar panel and the ambient temperature, is negative before 6:00 AM, during which the plant did not generate any output. As the irradiance is increased, the temperature of the solar panel increases resulting in increased temperature difference. The temperature difference of a solar plant beyond a rated limit this may result in decrease in efficiency over a period of time. The analysis of a solar power plant conducted on a weekly and monthly basis yielded for all different month, the results that were nearly identical. This finding suggests that the plant's performance is consistent over time and not significantly affected by fluctuations in solar irradiance or other variables.

C. *Comparative Analysis of Units with Optimization*

The accuracy of the model cannot be improved using the SVM regressor despite extensive analyses to comprehend the



(a) (b)

(c) (d)

Fig. 9: Hourly Analysis for (a) DC Power, (b) Temperature Difference, (c) Daily Yield and (d)Irradiance.

system for selecting the hyperparameter of the model due to the erratic pattern and unpredictability in climatic conditions and hence the output power produced by DERs. The mean square error of the wind unit is 74528.26 and solar unit is 2151.25 which is very high.

Using the Whale Optimization Algorithm (WOA) to optimise the mean squared error (MSE) was significantly reduced for the wind unit from an initial value of 74528.26 to 5.40 and for the solar team from an initial MSE of 2151.25 to an absolute value of 2.37. These improvements in MSE suggest

TABLE I: ERROR ANALYSIS USING WOA

	MSE without WOA	MSE with WOA
Wind Unit	74528.26	5.40
Solar Unit	2151.25	2.37

an increase in the accuracy of the model. MSE is reduced by comparing a given whale's position to those of other whales in the population and choosing the one that is most likely to result in a decrease in the MSE. The whales are first given random positions, which are then updated based on the best solutions from the target so far, the current position, and the social interactions with other whales. The algorithm involves iteratively updates the position of whales based on their performance observed by calculating the fitness for objective function. Through this process, the WOA algorithm searches for the optimal solution that minimises the MSE.

V. CONCLUSION

By analysing past data on energy consumption through time series analysis, it is possible to make accurate predictions about future demand. This can aid in streamlining the generation and distribution of electricity, ensuring that there is a sufficient supply to meet demand. In this paper, a problem involving the forecasting and scheduling of power from wind and solar units was addressed using a machine learning framework made by the combination of support vector machine (SVM) and the Whale Optimization Algorithm (WOA). These variables exhibit highly irregular and non-linear behavior, which makes it difficult to predict them with precision. Support Vector Machine proved to be good regressor for such datasets and high MSE of the model was reduced using optimisation technique that has also demonstrated effectiveness in solving scheduling plans in this context. A combination of SVM and WOA provides a reliable and efficient solution for predicting wind unit power, and solar unit power.

REFERENCES

[1] J. J. Justo, F. Mwasilu, J. Lee, and J.-W. Jung, "Ac-microgrids versus dc-microgrids with distributed energy resources: A review," *Renewable and sustainable energy reviews*, vol. 24, pp. 387–405, 2013.

[2] A. T. Elsayed, A. A. Mohamed, and O. A. Mohammed, "Dc microgrids and distribution systems: An overview," *Electric power systems research*, vol. 119, pp. 407–417, 2015.

[3] C. Liu, "A review of microgrid development and technology," in *IOP Conference Series: Earth and Environmental Science*, vol. 300, no. 4. IOP Publishing, 2019, p. 042048.

[4] K. Jithin, P. Haridev, N. Mayadevi, R. H. Kumar, and V. Mini, "A review on challenges in dc microgrid planning and implementation," *Journal of Modern Power Systems and Clean Energy*, 2022.

[5] Q. Xu, Y. Xu, Z. Xu, L. Xie, and F. Blaabjerg, "A hierarchically coordinated operation and control scheme for dc microgrid clusters under uncertainty," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 273–283, 2020.

[6] A. J. Smola and B. Schölkopf, "A tutorial on support vector regression," *Statistics and computing*, vol. 14, no. 3, pp. 199–222, 2004.

[7] G. Yuan, H. Wang, E. Khazaei, and B. Khan, "Collaborative advanced machine learning techniques in optimal energy management of hybrid ac/dc iot-based microgrids," *Ad Hoc Networks*, vol. 122, p. 102657, 2021.

[8] H. Xian and J. Che, "Unified whale optimization algorithm based multi-kernel svr ensemble learning for wind speed forecasting," *Applied Soft Computing*, vol. 130, p. 109690, 2022.

[9] C. Ihedioha Ahmed and S. Dipak, "Application of scada in modeling of power distribution systems and induction motor," *International Journal of Trend in Research and Development*, vol. 3, no. 1, pp. 286–291, 2016.

[10] X. Lin, X. Yu, and W. Li, "A heuristic whale optimization algorithm with niching strategy for global multi-dimensional engineering optimization," *Computers & Industrial Engineering*, vol. 171, p. 108361, 2022.

[11] P.-F. Pai, K.-P. Lin, C.-S. Lin, and P.-T. Chang, "Time series forecasting by a seasonal support vector regression model," *Expert Systems with Applications*, vol. 37, no. 6, pp. 4261–4265, 2010.

[12] "A Wind Turbine Power Curve Control - Kaggle," https://www.kaggle.com/code/berkerisen/a-wind-turbine-power-curve-control, [Online; accessed 19-July-2022].

[13] "Solar Power Generation Data - Kaggle," https://www.kaggle.com/datasets/anikannal/solar-power-generation-data, [Online; accessed 19-July-2022].